Does history matter for the relationship between R&D, Innovation and Productivity?

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Abstract

This paper analyzes the relationship between R&D expenditures, innovation and productivity growth, taking into account the possibility of persistence in firms' behaviour. We study this relationship for a sample of Spanish manufacturing firms between 1990 and 2005, estimating a model with four equations: participation in technological activities, R&D intensity, the generation of innovations and the impact of these technological outputs on total factor productivity growth. Our results reflect the existence of true state dependence both in the decision of R&D investment and in the production of innovations. The omission of this persistence leads to an overestimation of the current impact of innovations on productivity growth. However, the presence of persistence in technological inputs and outputs entails current R&D activities having long–run effects on a firm's productivity.

Keywords*:* CDM model, productivity growth, persistence in R&D and innovation.

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1. Introduction

The analysis of productivity growth and its determinants is a classic topic in Industrial Economics. There is a large number of papers that study this question from an empirical point of view, pointing out the performance of technological activities as an essential source of firms' growth. Following the method proposed by Griliches (1979), some authors include a stock of knowledge capital as an additional input in the firm's production function. Recently, the idea that the growth of firms is more related to the results of technological activities than to the inputs used in them has generated some studies that directly analyze the impact of technological outputs (process and/or product innovations, patents…) on firms' productivity. Specifically, Crepon et al. (1998) developed a multi-equational model (hereafter the CDM model) that explains productivity growth by technological outputs and the latter by technological effort. Since the appearance of this seminal paper, many researchers have applied the same methodology to different European countries using essentially cross-sectional data from the Community Innovation Surveys (CIS Data)[1].

However, only a few studies have used panel data to perform the analysis, mainly due to information availability, and therefore there is little evidence about these decisions that take into account the dynamics in a firm's behaviour. Some exceptions are the papers by Cefis and Orsenigo (2001), Cefis (2003), Mañez-Castillejo et al. (2009), Peters (2009) and Raymond et al. (2009, 2010), which empirically analyze the persistence of R&D activities or technological outputs with different methodologies and results.

In this line, the objective and the main contribution of the present paper is to consider the existence of persistence both in the R&D investment decision and in the achievement of innovations when estimating the recursive model that reflects the relationship between R&D, innovations and productivity. With this aim, we adapt the CDM model to analyze this relationship for a panel of Spanish manufacturing firms between 1990 and 2005. Our econometric results suggest the existence of true state dependence both in the decision of R&D investment and in the production of innovations. The omission of this persistence in the

[1] See, for example, Mairesse and Mohnen (2002, 2005) and Mohnen *et al*. (2006) using French CIS1 and CIS3 data, Parisi *et al*. (2006) for Italian manufacturing firms, Lööf and Heshmati (2006) using Swedish manufacturing data, Van Leeuwen and Klomp (2006) and Polder et al. (2009) for Dutch manufacturing firms, Segarra (2010) for Catalan firms, and Griffith et al. (2006) using firm-level data from the internationally harmonized CIS3 for France, Germany, Spain and the UK. Two examples for non-European countries are Benavente (2006) for Chile and Jefferson et al. (2006) about China.

analysis leads to an overestimation of the current impact of innovations on productivity growth. However, the existence of true state dependence in technological inputs and outputs entails current innovation activities having long–run effects on a firm's productivity. This is especially important when analyzing the relevance of technological policy as an instrument to induce productivity increases.

Following this introduction, the next section presents the theoretical framework and the empirical multi-equational model. Section 3 describes the database and the variables included in the specification. The results of the estimation of the model are presented in Section 4 and, finally, Section 5 summarizes the main conclusions.

2. Theoretical framework and empirical model

Since the seminal contributions of Griliches (1979, 2000), many authors have analyzed the relationship between R&D activities and productivity, finding, in general, a positive and significant effect of R&D on productivity, although with different magnitudes depending on the methodology employed and the level of analysis[2]. In this respect, as Mairesse and Sassenou (1991) point out, the issue is not so much the question of whether or not such a relationship exists, but whether or not econometric studies can characterize such a relationship in a satisfactory and useful manner.

Going deeper with this idea and following Crepon et al. (1998), recent studies on this topic specify that the impact of R&D is transmitted to productivity growth through the generation of technological outputs. The abundant international evidence supporting the CDM model confirms the relevance of taking the indirect channels of influence of R&D activities into account. Another way of improving the measure of this impact has been to consider the existence of delayed or long-term effects. Two examples are the papers by Huergo and Jaumandreu (2004a) and Rochina et al. (2010). Using different techniques, they both find that the effect of process innovations on productivity growth persists somewhat over time. This effect is expected to be larger if, in addition, there is persistence in the firm's innovative behavior.

[2] See Mairesse and Sassenou (1991) for a survey and, more recently, the papers by Klette and Kortum (2004), Janz et al. (2004), Rogers (2006), Lööf and Heshmati (2006), among others.

In fact, the persistence of innovative activities plays an important role in the literature on industrial dynamics and endogenous growth, which provides theoretical arguments to explain the importance of this persistence (Nelson and Winter, 1982, Romer 1990, Aghion and Howitt 1992, Dosi et al., 1995, Malerba and Orsenigo, 1996). In the seminal contribution of Nelson and Winter (1982), industrial change is explained by an evolutionary approach. After radical innovations, the firms obtain incremental innovations along a technological trajectory. As consumers prefer new versions of old products, innovation by firms increases over time. Aghion and Howitt (1992) propose a model of economic growth based on the process of creative destruction by Schumpeter. In their model, growth depends only on technological progress generated by new intermediate goods. Because the revenue captured by a successful innovation is supplanted by the next innovation, firms are motivated to innovate persistently.

As for the Spanish case, there is ample empirical literature on industrial dynamics and firms' behavior that refers mainly to survival and market turbulence and that confirms the relevance of these elements for a firm's growth. Some interesting examples are Segarra and Callejón (2002), Esteve et al. (2004) and Ortega-Argilés and Moreno (2007).

In this paper, we want to analyze the R&D-productivity relationships, combining the CDM framework with a dynamic consideration of a firm's innovative behavior. That is, instead of considering a static framework, we model the firm's decision to engage in R&D activities and the equation for the generation of innovations with the possible persistence in these stages taken into account.

As Heckman (1981) points out, there are two explanations for persistent behaviour: the true state dependence and the spurious dependence. The first one implies a real causal effect: the probability of investing in *t*-1 increases the probability of investing in *t*. There are some theoretical explanations for this real true dependence in the case of innovation activities (Peters, 2009): the sunk cost associated with the performance of R&D activities, the "success breeds success" hypothesis and the existence of dynamic increasing returns. Alternatively, some firm characteristics can positively affect the decision to engage in R&D activities or the generation of innovations and, if they are correlated over time, could also create a spurious relation between current and future status (spurious dependence). Some of them can be observables, like size, and it is possible to control them in the empirical analysis. However, there are other characteristics, like managerial ability, technological opportunities and risk attitudes that are unobservable. If these characteristics are persistent over time and they are not properly treated in the estimation, they can generate a spurious state dependence in R&D activities.

According to these theoretical explanations for real state dependence, it is not clear whether persistence is more related to technological inputs or outputs. Under the sunk cost hypothesis, R&D decisions are modeled in a long-term horizon, given that sunk costs could represent not only a barrier to entry for new firms, but also a barrier to exiting for incumbent firms that have not recovered their investments. In this case, an input measure would be desirable. However, the "success breeds success" and the "learning by doing" hypotheses are more associated with technological results. Additionally, if we assume that innovation outputs are in part determined by innovation inputs, input persistence should be translated partially into output persistence[3].

The empirical evidence about this question is mixed. Mañez-Castillejo et al. (2009) study the persistence in the firm R&D status, i.e., in the decision to engage in R&D activities, while Peters (2009) analyzes whether firms innovate persistently, defining an innovator as a firm which exhibits positive innovation expenditure in a given year. In contrast to these studies, Duguet and Monjon (2004) and Raymond et al. (2010) examine the persistence in innovation outputs, although, as they use CIS data, their indicators as to whether a firm has introduced an innovation are related to a 3–year period, which could induce an artificial persistence due to overlapping time periods and double counting (Peters, 2009). However, Raymond et al. (2010) find that there is only true persistence of innovation in high-technology industries. For low-technology industries, past process and product innovations and past shares of innovative sales do not affect current process and product innovations and innovative sales[4]. In another related paper, Raymond et al. (2009) study the dynamics in innovation inputs and outputs, estimating a dynamic panel data bivariate Tobit model. They obtain persistence in both and a feedback effect of innovation output on innovation input in all industries.

[3] There are also firm characteristics (ownership, capital structure, maturity), knowledge spillovers or other appropriability variables external to the firm (determined by location or market characteristics), as well as complementarities among internal and external determinants, that exert an important effect on the firm's innovative behaviour.

[4] Although their objective is not properly the analysis of persistence, Piva and Vivarelli (2007) also consider lagged R&D expenditures as an explanatory variable when studying the effect of demand evolution on R&D expenditures according to different groups of firms.

Our paper differs from previous ones in the sense that we analyze the persistence in both input and output R&D activities in a recursive model[5]. Nevertheless, we do not consider the dynamics of the R&D intensity (R&D expenditures over employment), but only in the decision to engage in R&D activities. In what follows, we describe how the introduction of persistence affects each of the stages of our adapted CDM model, which includes four equations**.** The first equation describes the firm's decision to engage in technological activities or not. The second one refers to the intensity of technological inputs (measured basically by the intensity of the R&D expenditure). The third equation deals with the generation of innovations on the basis of both internal and external technological inputs and, finally, the fourth equation shows the impact of these innovations on productivity growth, measured by the Solow residual.

2.1. R&D equations

Following the approach of Griffith et al. (2006), we believe that, to some extent, all firms make some innovative effort. However, below a certain threshold, the firm is not capable of picking up explicit information about this effort and will not report on it. Thus, we estimate a selection model for the observed R&D intensity.

In particular, we think that we can measure the R&D effort id_{it}^{*} by the intensity of the R&D expenditure id_{it} only if the firm makes and reports that expenditure. To represent this decision to perform and report R&D expenditures, we assume the following selection equation:

$$r_{it} = \begin{cases} 1 & \text{if} \quad r_{it}^{*} = \gamma \cdot r_{it-1} + x_{1it}{'}\beta_1 + \mu_i + u_{1it} > 0 \\ 0 & \text{if} \quad r_{it}^{*} = \gamma \cdot r_{it-1} + x_{1it}{'}\beta_1 + \mu_i + u_{1it} \le 0 \end{cases} \qquad [1]$$

, where r_{it} is a binary variable that takes the value 1 when the firm invests in (and reports) R&D, and 0 otherwise. If the latent variable r_{it}^{*} is bigger than a constant threshold (which can be zero), we then observe that the firm engages in (and reports) R&D activities. In this equation, r_{it-1} captures the previous innovation experience (true state dependence), x_{1it} is a vector of observable explanatory variables (time-variant and time-invariant variables) and the

[5] With the aim to jointly analyze the dynamics of trade and innovation, Esteve and Rodríguez (2009) present estimations for R&D performance, product and process innovations as “alternative" measures of the innovation status. Their results indicate the existence of true state dependence in both export and innovation.

permanent unobserved heterogeneity is captured by μ_i. Finally, u_{1it} is an idiosyncratic error (which refers to other unobservable time-variant determinants).

To estimate this dynamic equation, we have to solve two theoretical and empirical problems: how to treat the unobservable heterogeneity (μ_i) and the treatment of initial conditions (r_{i0}). With respect to the first problem, a fixed effects (FE) or a random effects (RE) model can be used to model μ_i. Following Mundlak (1978) and Hsiao (2003), we prefer a random effects model for two reasons. It allows for treating omitted factors that affect the dependent variable as random errors instead of constants. Furthermore, with this methodology, we can make inferences about all the unobservable effects in the population, and not only in the sample, as would be the case with a fixed effects model.

The second problem arises because the first observation of each firm (initial condition) is affected by the same generation process and for this reason is endogenous. Among the different ways to solve this problem, we follow the method suggested by Wooldridge (2005), who develops an estimator for dynamic non-linear RE models where it is necessary to model the unobservable heterogeneity[6]. Specifically, we assume that this unobserved individual heterogeneity depends on the initial conditions and the strictly exogenous variables:

$$\mu_i = \alpha_1 + \alpha_2 \cdot r_{i0} + \overline{x}_{1i}{}'\alpha_3 + a_i$$

, where $\overline{x}_{1i}$ is the time-average of x_{1it} and where r_{i0} is the initial value. The assumptions about a_i are $a_i \cong i.i.d.\ N(0, \sigma_a^2)$ and $a_i \perp (r_{i0}, \overline{x}_{1i})$.

In the original estimator proposed by Wooldridge (2005), instead of the average of the exogenous variables, he uses all the time observations of the variables. However, he shows that time-averages can be used to reduce the number of explanatory variables.

Therefore, under this parameterization, the probability of being a firm which engages in (and reports) R&D activities is:

6 This method was proposed by Chamberlin (1980) for a linear AR(1) model without covariates. Another solution is to assume that the initial condition is a non-random constant and therefore is uncorrelated with the unobservable heterogeneity. However, this assumption is very unrealistic. Alternatively, we could consider r_{i0} to be random and try to estimate the joint density for r_{i0} and for all r_{it} conditioned to the strictly exogenous variables. Although Heckman (1981) proposes a method for approximating the conditional distribution, this function can only be found in some special cases.

$$r_{it} = \begin{cases} 1 & \text{if} \quad r_{it}^{*} = \gamma \cdot r_{it-1} + x_{1it}{'}\beta_1 + \alpha_1 + \alpha_2 \cdot r_{i0} + \overline{x}_{1i}{'}\alpha_3 + a_i + u_{1it} > 0 \\ 0 & if \quad r_{it}^{*} = \gamma \cdot r_{it-1} + x_{1it}{'}\beta_1 + \alpha_1 + \alpha_2 \cdot r_{i0} + \overline{x}_{1i}{'}\alpha_3 + a_i + u_{1it} \leq 0 \end{cases} \qquad [1']$$

Conditional on the performance (and reporting) of R&D activities, we can observe the quantity of resources allocated to this purpose; that is,

$$id_{it} = \begin{cases} id_{it}^{*} = x'_{2it}\beta_2 + u_{2it} & \text{if} \quad r_{it} = 1 \\ 0 & \text{if} \quad r_{it} = 0 \end{cases} \qquad [2]$$

, where x_{2it} is a vector of determinants of the innovative effort, which can differ from those determinants that explain the decision to perform and report R&D expenditures.

Therefore, to capture the true impact of R&D intensity on knowledge production, we estimate a selection model for the observed intensity and to use the predicted value as a proxy of the innovation effort in the production function of knowledge or innovations. However, to our knowledge, there is not any commonly accepted econometric procedure that integrates the intensity equation [2] and Wooldridge's (2005) approach for estimating a dynamic RE model for equation [1'] in a selection model.

For this reason, we start with the estimation of a Heckman model where a static pooled model for the first decision is considered. That is, we implicitly assume that there is not state dependence ($\gamma = 0$) and the unobservable individual heterogeneity is not parameterized. Secondly, we consider a dynamic pooled Probit for the decision whether to engage in R&D activities or not, where the individual heterogeneity is parameterized as in Wooldridge (2005). In both cases, we assume that the error terms u_{1i} and u_{2i} follow a bivariate normal distribution with a mean equal to 0, variances $\sigma_1^2 = 1$ and σ_2^2, and correlation coefficient ρ_{12} (Rho). Finally, as a robustness check, we compare the results for the selection equation in the second case with the estimation of a dynamic RE Probit model where individual heterogeneity is parameterized following Wooldridge (2005).

2.2. Knowledge equation

The third equation of the model corresponds to the estimation of the new knowledge production function, g_i, generated from firms' technological effort. This new knowledge is measured alternatively by three dummy variables that capture, respectively, the achievement of product innovations, process innovations, and any of them[7]. Given that the investment intensity is a public good within the firm, it can be used to produce different outputs without depletion. Therefore, we can model g_{it} as a vector of technological outputs:

$$g_{it} = \delta \cdot g_{it-1} + \lambda \cdot id_{it}^{*} + x_{3it}'\beta_3 + \zeta_i + u_{3it} \qquad [3]$$

, where the latent investment intensity id_{it}^{*} appears as an explanatory variable joint with the vector x_{3it}, which includes other determinants of the knowledge production (time-variant and time-invariant variables). We also add the dependent variable lagged one period, g_{it-1}, in the specification to reflect whether the firm has previously generated new knowledge capturing the innovation output experience.

As in equation [1], following Wooldridge (2005), we model the unobserved heterogeneity ζ_i as dependent on the initial conditions and the average of the explanatory variables:

$$\zeta_i = \pi_1 + \pi_2 \cdot g_{i0} + \overline{x}_{3i}'\pi_3 + \upsilon_i$$

We assume that $\upsilon_i \cong i.i.d.\, N(0,\sigma_\upsilon^2)$ and $\upsilon_i \perp (g_{i0}, \overline{x}_{3i})$. Therefore, the new knowledge production function can be expressed as:

$$g_{it} = \delta \cdot g_{it-1} + \lambda \cdot id_{it}^{*} + x_{3it}'\beta_3 + \pi_1 + \pi_2 \cdot g_{i0} + \overline{x}_{3i}'\pi_3 + \upsilon_i + u_{3it} \qquad [3']$$

Given that our measures of new knowledge generation are binary variables for process or product innovation, the last equation will be estimated by a dynamic RE Probit model.

2.3. Productivity equation

Our productivity equation starts by assuming a production function for firm *i* in year *t* of the type:

$$Y_{it} = A_{it} \cdot F(L_{it}, K_{it}, M_{it})$$

where *Y* denotes the quantity of output, *L*, *K* and *M* are, respectively, the quantities of labor, physical capital and materials, and *A* represents the level of efficiency reached by the firm,

[7] Other measures of innovation outputs have been used in complementary estimates of the knowledge production function. Specifically, we have considered dummy variables for the joint generation of product and process innovations, for only process and for only product innovators. The results confirm those presented in this paper and are available from the authors upon request.

which implies Hicks neutrality of productivity increases and can be interpreted as an unspecified function of knowledge[8].

By differentiating the last expression, we obtain:

$$y_{it} = a_{it} + \varepsilon_{y,l} \cdot l_{it} + \varepsilon_{y,k} \cdot k_{it} + \varepsilon_{y,m} \cdot m_{it} + u_{4it}$$

where y, l, k and m stand respectively for the logarithmic differences in production and in the quantities of labor, physical capital and intermediated inputs, $\varepsilon_{y,l}$, $\varepsilon_{y,k}$ and $\varepsilon_{y,m}$ are the output elasticities with respect to the above inputs, and a is the productivity growth, which in part will be determined by the technological output ($a_{it} = a(g_{it})$). u_{4it} stands for a disturbance which we assume to have zero mean conditional on the included variables.

Under the assumption of constant returns to scale, cost minimization implies that input elasticities equal cost shares. Therefore, we can re-write the prior expression as:

$$y_{it} = a(g_{it}) + s_l \cdot l_{it} + s_k \cdot k_{it} + s_m \cdot m_{it} + u_{4it}$$

where s denotes cost shares. Rearranging terms, it is possible to transform the last expression into a equation that relates the well-known observable (cost shares-based) Solow residual, θ_{it}, to the productivity increases generated by new knowledge:

$$\theta_{it} = y_{it} - (s_l \cdot l_{it} + s_k \cdot k_{it} + s_m \cdot m_{it}) = a(g_{it}) + u_{4it}$$

Based on this expression, our estimable equation will be:

$$\theta_{it} = \varpi \cdot g_{it} + x_{4it}'\beta_4 + u_{4it} \qquad [4]$$

where x_{4it} is a vector that includes the variables reflecting the non-fulfillment of the assumptions associated with this kind of model (constant returns to scale, instant adjustment of the inputs), along with other control variables. In the estimation of this last equation, we will take into account the potential endogeneity of the technological output g.

To summarize, our model consists of equations [1'], [2], [3'] and [4]. Following the CDM methodology, we assume a recursive model where feedback from productivity growth to technological effort is not allowed, and therefore we apply a three-stage estimation procedure.

[8] A similar approach is used in Huergo and Jaumandreu (2004b) to link productivity growth with the firm's age and innovation.

3. Data and variables definition

Estimations are carried out with an unbalanced panel of Spanish manufacturing firms for the period 1990-2005[9]. The variables are obtained from the *Encuesta Sobre Estrategias Empresariales* (ESEE), a survey that is sponsored by the Spanish Ministry of Industry and carried out by the Fundación SEPI[10]. The sampling scheme of this survey is conducted for each manufacturing NACE class (two-digit) level. Companies employing between 10 and 200 employees are chosen by a random sampling scheme and the rate of participation is around 4%. For firms employing more than 200 employees, the rate of participation is about 60%. The sample considered is about 2000 manufacturing firms that have ten or more employees each year.

Table 1 shows the main characteristics of the database distinguishing between small and medium-sized firms (SME) (with fewer than 200 workers) and large firms (more than 200 employees). To analyze the dynamics of R&D activities, it is required that the firms answer consecutively. In this sense, only those firms that have at least eight consecutive observations, which is the average period of our sample, have been taken into account. As can be seen in Table 1, in our unbalanced panel the average number of consecutive years per firm is around 12. We could restrict the analysis to the balanced panel, but due to attrition in this case we lose two thirds of the observations.

Although the ESEE is not specifically designed to analyze technological activities, it includes a relevant set of indexes about this subject and has information not only for firms engaged in technological activities but also for firms without R&D expenditures. In fact, for the analysis we have 12,303 observations and 7,548 of them correspond to firms that do not perform formal R&D. This is especially suitable in this case, given that we assume that all firms make some innovative effort, although not all reflect this effort in their answer to the survey. That's why we estimate the model for the whole sample, and not only for firms with positive R&D expenditures. As a measure of the R&D investment intensity, we use the total R&D

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[9] The information currently available in the database is up to 2008, but this was not the case when we started this work. However, as we have data for a very long period (15 years), we think this is enough for our purposes.

[10] This database has been already used for innovation purposes. Some examples are Huergo and Jaumandreu (2004a and b), Máñez-Castillejo et al. (2009) and Artés (2009). See a more detailed description of the ESEE in http://www.funep.es/esee/en/einfo_que_es.asp, where the full questionnaire is also available.

expenditure per employee (in logs), assuming that a firm decides to perform technological activities if its expenditures are positive.

Table 1

Characteristics of the sample

	Firms with at least eight consecutive observations		
	SME	Large Firms	All Firms
No. of observations	8052	4251	12303
No. of firms	709	363	1072
Average no. of consecutive observations by firm	12.0	12.3	12.1

Table 2 presents the transition probabilities of engaging in R&D activities or not over the period 1990-2005. Notice that the status in *t*-1 is positively correlated with the status in *t*. Almost 90% of firms which perform R&D activities in one year persist in the following year. Additionally, more than 93% of non-performing firms in *t*-1 are also non-performers in *t*, while 7.3% engaged in R&D activities. This implies that the probability of undertaking R&D in *t* is 82 percentage points higher for performers than for non-performers in *t*-1[11].

Table 2

Transition probabilities of the R&D status

		Performer in t	
	Performer in t-1	Yes	No
SME	Yes	83.2	16.8
	No	5.0	95.1
Large Firms	Yes	92.7	7.3
	No	15.5	84.5
All Firms	Yes	89.1	11.0
	No	6.9	93.2

Following theoretical models (Arvanities and Hollenstein, 1994, Klepper, 1996), the variables to be included in the participation and the intensity equations relate basically to the technological environment, demand and market conditions, appropriability of the benefits

[11] When the balanced panel is considered, the transition probabilities of the R&D status are almost the same.

derived for technological investments[12], financial restrictions and size (to capture the existence of economies of scale in R&D).

In this line, given the available information in the database, to capture environmental and demand conditions, we have introduced, as explanatory variables, one indicator of the firm's export character and a variable reflecting whether the market evolution perceived by the firm each year was expansive or recessive with respect to the previous year.

Following Schumpeterian tradition, we include a qualitative measure of the number of a firm's rivals to capture the degree of market competition.[13] A negative impact of this variable on the participation decision would be coherent with the hypothesis that the more competitive the market, the less capacity firms have for appropriating the benefits of their investments, and therefore have fewer incentives to make these investments. However, later theoretical approaches support the idea that firms in competitive markets can obtain bigger gains from innovation than monopolistic firms (see Artés, 2009, for a summary). Other papers combine both arguments to explain an inverted-U relationship. For example, Aghion et al. (2005) develop a model where competition encourages neck-and-neck firms to innovate due to the higher incremental profits of innovation in competitive markets. However, innovation will decrease when the level of competition increases as it discourages laggard firms from innovating. Levin et al. (1985) also provide empirical evidence of this inverted U-relationship, but when they control for technological and appropriability conditions, the effect of market structure is smaller or even disappears.

To indicate appropriability conditions, we have used the proportion of engineers and graduate employees in the firm as a measure of human capital. We can think that those firms with more qualified personnel are more capable of assimilating new knowledge, whether it is developed internally or externally. Piva and Vivarelli (2009) provide evidence that supports this hypothesis for a panel of Italian firms. In addition, following previous papers for the Spanish economy, we introduce industry dummies that can also approach sectoral technological opportunities and appropriability conditions (Beneito, 2003, Ortega-Argilés et al., 2005).

[12] See in Cohen and Levin (1989) a discussion about the effect of technological opportunities, appropriability conditions and market evolution on R&D activities.
[13] The concentration ratio CR4 is also available in the database, but with a very low response.

With respect to financial restrictions, we use a categorical variable that shows whether the firm obtained public support during the year. The high level of risk of R&D projects and the existence of information asymmetries between firms and suppliers of external finance increase the firms' dependence on internal funds (Hall, 2002). Therefore, firms with liquidity constraints are expected to have more difficulties undertaking R&D projects.

The evidence about the impact of financial restrictions on investment effort is mixed. The results by Hall (1992) and Himmelberg and Petersen (1994) suggest a positive relationship between cash flow and R&D expenditures for different samples of American manufacturing firms. Hall et al. (1999) also find that during the period 1978-1989, R&D in the American high-tech sector was sensitive to cash flow, while the results are not so clear in the case of France and Japan. Bond et al. (1999) find that the cash flow affects the decision to perform R&D more than the levels of expenditure for the UK. Previous works for Spanish economy point out that, irrespective of firm size, the investment effort since 2000 has been superior in firms that won public support than in those who apply for it without success, and greater in the latter than in firms that did not apply for it.

Along with the above variables, the specification includes indicators to capture differences in the firms' investment behavior in terms of the time of permanence in the market. According to the theoretical model developed by Keppler (1996), the number of innovations per firm at a given moment will be higher the younger the cohort is. Hence, we should find a negative relationship between the firm's age and its probability of innovating. However, the firm's age can also be a measure of the experience and the knowledge accumulated throughout the history of the firm and in this sense it should be positively related to innovation (Galende and De la Fuente, 2003). In addition, international evidence suggests that entrants are among the most innovative and that the growth rate post-entry depends on their innovative behavior, the probability of survival being tied to the existence of technological opportunities (Audretsch, 1995, and, for Spanish industry, Huergo and Jaumandreu, 2004b). To test this relationship in our model, we introduce the firm's age and two dummies reflecting whether the firm was an entrant or an exiting firm during the period. The set of mobility indicators is fulfilled with two event dummies for mergers and scissions.

Finally, we include sets of time and size dummies as control variables in both equations, and two factors related to firms' organizational aspects: belonging to a society and the degree of services subcontracting. As Raymond et al. (2009) point out, firms that are part of a group can be more innovative because they benefit from internal financing, knowledge spillovers and marketing synergies.

As for the knowledge production function, the ESEE provides qualitative information about the achievement of process and product innovations. In particular, a product innovation is assumed to have occurred when the firm answers the following request in the affirmative: “Please indicate if during the year 199x your firm obtained product innovations (completely new products or products with such important modifications which made them different from the old ones)”. In a similar way, a process innovation is assumed to have occurred when the firm answers the following request positively: “Please indicate if during the year 199x your firm introduced some significant modification in the production process (process innovation). If the answer is yes, please indicate the way: a) introduction of new machines; b) introduction of new methods of organization; c) both.”

Table 3 shows the transition probabilities for the generation of product or process innovations during the sample period. In both cases, the status in *t*-1 is positively correlated with the status in *t*, although the persistence seems to be slightly higher for product innovations. Almost 70% of firms which innovate in one year persist in innovating the following year, while more than 82% of non-innovative firms in *t*-1 are also non-innovators in *t*. This confirms the interest in taking persistence into account when analyzing the generation of new knowledge.

Table 3
Transition probabilities of the innovator status

		Innovator in t			
		Process Innovator		Product Innovator	
	Innovator in t-1	Yes	No	Yes	No
Small and medium firms	Yes	60.3	39.7	65.9	34.1
	No	14.8	85.2	8.5	91.5
Large Firms	Yes	75.6	24.4	73.7	26.3
	No	23.7	76.3	15.9	84.1
All Firms	Yes	67.6	32.4	69.7	30.3
	No	17.2	82.8	10.7	89.3

The ESEE provides information about other different measures of technological results (number of product innovations, patents and utility models). Our selection in terms of dummies for process and product innovations is mainly based on two reasons**.** Firstly, the database does not include information about the number of process innovations. Therefore, the quantitative information about the number of product innovations would imply an asymmetric treatment with respect to process innovations, making the interpretation and comparison of their coefficients in the productivity equation difficult. Secondly, in the database, the rate of response of the questions related to utility models and patents is lower than the one related to product and process innovations[14]. In addition, we think that "patents" and "utility models" are less informative about the innovation results of Spanish firms. With respect to the application for patents, this mechanism is rarely used by Spanish firms. Only 6% of the observations in our sample correspond to firms which apply for patents in Spain and this percentage is even lower (4%) for international patents[15]. Therefore, we think that our innovation dummy measures better reflect the generation of new knowledge by Spanish companies.

With respect to the explanatory variables in the knowledge production function, in the case of process innovations, given that these can be obtained by buying new machines, along with investment effort we include physical capital intensity (in logs). In addition, irrespective of the type of innovation, the set of variables also comprises specific industry characteristics. Following Ortega-Argilés et al. (2010), we expect that firms in high-tech sectors not only invest more in R&D, but also achieve more results from their research activities[16]. Notice that, along with internal inputs, it is also necessary to take into account other elements that do not depend completely on the firms' decision but can affect their generation of innovations. In particular, the incentives to allocate resources can change depending on demand price elasticity. In markets where the product supplied by the firm is highly standardized, product innovations are a better mechanism for reducing competitive pressure. In the estimations, we use a binary variable reflecting the degree of product homogeneity as a "naive" proxy of demand price elasticity. This index takes the value one if the product sold by the firm is highly standardized. The specification also includes industry dummies to capture the possibility of technological spillovers and different life cycles and technological regimes (Klepper, 1996, and Utterback, 1994).

[14] Using the former variables would imply losing more than 1,500 observations.

[15] With respect to utility models, while the percentage of firms in our sample that report process or product innovations is about 44%, this percentage is reduced to 3% in the case of utility models.

[16] In Ortega-Argilés et al. (2010) these results are measured in terms of labour productivity.

As for productivity growth (equation [4]), the available information allows us to compute a cost-based Solow residual in terms of a Tornqvist index[17]. According to data availability, in previous literature we find different proxies for productivity that include labor productivity measured as the ratio between value added and employment or hours worked, total factor productivity, Solow's residual, etc. The measure we employ in this paper is equivalent to the measure of Total Factor Productivity (TFP) growth used by Huergo and Jaumandreu (2004a) to link process innovations to productivity growth of Spanish firms. Starting from the same database, Rochina et al. (2010) also construct a measure of TFP growth at the firm level, although they prefer to define a multilateral productivity index. However, in papers that apply the CDM model using the Spanish version of the CIS, the measure of performance is labor productivity defined as the ratio between turnover and employment (Griffith et al., 2006, Segarra, 2010). As we will see later on, the selection of the dependent variable in the productivity equation is relevant to capturing significant effects for the different types of innovations.

In this equation, together with the technological output and the control variables (mobility, time, size and industry dummies), we introduce the change in the capacity utilization to pick up the impact in the degree of inputs used in the presence of quasi-fixed factors. In addition, we include the weighted input variation to capture the potential bias by the non-fulfillment of the constant returns to scale assumption[18].

Table 4 shows the descriptive statistics of the main variables in our model. Except the degree of services subcontracting, all of them can vary across firms and time. Note that, for almost all explanatory variables to be used in the selection equation, the variation across firms ("*between*" variation) is bigger than the time variation ("*within*"). See, for example, the age, the degree of services subcontracting and the number of competitors. For this reason, we are going to treat them as time constant in equation [1'].

[17] In the ESEE, firms report the price changes on their output and inputs, which makes it possible to construct Paasche-type firm individual indices to deflate output and intermediate consumption real changes.
[18] See the Appendix for a more detailed explanation of the variable definitions.

Table 4
Descriptive Statistics

	Mean	Standard deviation			Min	Max
		Overall	Between	Within		
Age	24.781	12.297	12.077	3.038	1	40
Belonging to a group	0.324	0.468	0.427	0.197	0	1
Capacity utilization variation (%)	0.077	15.739	2.591	15.539	-230.259	289.037
Degree of product homogeneity	0.636	0.481	0.429	0.226	0	1
Degree of services subcontracting	47.013	11.215	11.345	0.000	0	93.4
Demand evolution	2.113	0.689	0.367	0.588	1	3
Export intensity in t-1 (in logs.)	6.226	4.861	4.473	1.933	0	13.637
Exporter in t-1	0.640	0.480	0.425	0.227	0	1
Human capital (% of engineers and graduates)	4.165	6.512	6.308	2.244	0	78.9
Number of competitors	1.787	1.113	0.884	0.692	1	4
Physical capital intensity (in logs.)	9.746	0.948	0.885	0.367	7.118	12.644
Process innovation	0.352	0.478	0.295	0.377	0	1
Product innovation	0.266	0.442	0.300	0.325	0	1
Public support in t-1	0.100	0.300	0.217	0.205	0	1
R&D intensity	2.683	3.509	3.059	1.720	0	11.142
R&D performer	0.387	0.487	0.414	0.255	0	1
Size (number of employees)	216.2	463.5	463.5	103.9	3	9043
Total factor productivity growth (%)	0.810	14.435	2.907	14.154	-208.197	170.461
Weighted inputs variation (%)	2.873	21.327	6.355	20.427	-161.171	310.349

Notes: The period used is 1991-2005. For lagged variables the reference period is 1990-2004.

4. Econometric results

In this section, we present the results of the estimation of the model depicted in Section 2. As equations [1] to [4] point out, we assume a recursive model where feedback from productivity growth to technological effort is not allowed. Taking this into account, we apply a three-stage estimation procedure.

In the first stage, the decision to engage in R&D activities is jointly estimated with the R&D intensity (equations [1] and [2]) using the Generalized Tobit model. We investigate the possibility of persistence in the selection equation but we do not consider any dynamics in the R&D effort. In particular, we use Wooldridge's (2005) approach to parameterize the unobserved individual heterogeneity.

In the second stage, we estimate the knowledge production function [3], introducing the predicted value of the R&D intensity as an explanatory variable. As we indicate in Section 2, the technological effort can be used to obtain new products and/or processes. Therefore, we consider both types of innovations to be technological outputs. Additionally, we study whether the probability of obtaining a process or product innovation is positively affected by previous success in the generation of innovations. Given the binary character of our innovation indexes, we estimate this equation as dynamic RE Probit models. As in the first stage, Wooldridge's approach is used to parameterize the unobserved individual heterogeneity.

Finally, in the last stage, the productivity growth equation [4] is estimated taking into account the potential endogeneity of the technological factor in the production function.

R&D investment intensity

Table 5 shows the results of the estimation associated with equations [1] and [2] explained in Section 2. We start with the estimation of a pooled and static RE Probit model**,** implicitly assuming no state dependence in the selection equation ($\gamma = 0$). In columns (1) and (4), we present the results of the Generalized Tobit model where the participation and the intensity equations are estimated consistently by maximum likelihood.

Secondly, in column (2), we investigate the persistence of the decision whether to engage in R&D activities or not by estimating this equation as a dynamic RE Probit model (equation [1']), following Wooldridge's approach for taking into account the unobservable individual heterogeneity. Finally, given that we confirm the existence of true state dependence in the selection equation, a Generalized Tobit model is estimated**,** parameterizing the individual unobserved heterogeneity in terms of the initial conditions and the exogenous variables (columns (3) and (5)) as in the dynamic RE Probit model.

The three first columns exhibit the marginal effects of the Probit model for the participation decision, while the coefficients showed in columns 4 and 5 correspond to the R&D intensity for the static and dynamic pooled model, respectively. Notice that the correlation term rho (ρ_{12}) is significant in both estimations, pointing out the necessity of estimating a selection model for the observed intensity.

We tried almost the same set of explanatory variables for both equations ($x_{1it} = x_{2it}$), but eventually we included only those variables that turn out to be statistically significant in each equation in the specification. There are four variables, the firms' age, the human capital[19], the degree of services subcontracting and the number of competitors, which present a very small *within*-firm variation. Due to the high collinearity between them and their time-averages, when we introduce the last ones in the parameterization of the individual heterogeneity, none are significant. This implies that these variables cannot be included in the parameterization of the individual effects[20].

Additionally, the dynamic RE Probit model requires the strict exogeneity of the explanatory variables. Although it is possible to assume that most variables are exogenous, the indicators for being an exporter and for the winning of public support are introduced with a lag in the decision equation to control for endogeneity.

With respect to the decision to engage in (and report) R&D activities, the estimation in column (2) confirms that it is relevant to consider the existence of persistence. Even after controlling for individual unobserved heterogeneity, previous behavior as an R&D performer has a positive effect on the probability of engaging in R&D activities at present. That is, conditional on other firms' characteristics, a firm which performs R&D in *t*-1 is almost 60 percentage points more probable to undertake R&D activities in the next period.

The initial conditions are also significant, which suggests the existence of a high correlation between the initial value and the unobserved heterogeneity. In particular, the achievement of public support and being an exporter in the previous period have a positive impact on the probability of innovating. Additionally, the coefficient of correlation ρ_a at the bottom of column (2)[21] indicates that the unobserved heterogeneity explains 12% of the total variance of the dependent variable[22].

[19] In the survey, firms only answer the question referring to this variable every four years.
[20] In fact, after several attempts, the model that provides the best identification of the parameters seems to be the one in which the age and the number of competitors are considered to be time-constant specific variables in the estimation for the participation equation. These results are presented in Table 5.
[21] ρ_a is $\frac{\sigma_a^2}{1+\sigma_a^2}$ and shows the percentage of total variance explained by the unobserved heterogeneity.
[22] When estimating the equation through a Static RE Probit model, unobserved heterogeneity is relatively more important: almost 75% of the variance is explained by it.

Table 5

R&D intensity

	Propensity to engage in R&D (0/1)			R&D Intensity	
	(1)	(2)	(3)	(4)	(5)
Estimation method	*Pooled Probit*	*Dynamic RE Probit*	*Dynamic Pooled Probit*	*Generalized Tobit (selection from (1))*	*Generalized Tobit (selection from (2))*
R&D performer in t-1		0.586***	0.638***		
		(0.016)	(0.012)		
Exporter in t-1	0.197***	0.039	0.032		
	(0.012)	(0.029)	(0.028)		
Export intensity in t-1				0.032***	0.016***
				(0.006)	(0.006)
Public support in t-1	0.535***	-0.022	-0.066**	0.678***	0.625***
	(0.018)	(0.032)	(0.029)	(0.048)	(0.050)
Demand evolution	0.048***	0.039***	0.037***	0.066***	0.083***
	(0.008)	(0.012)	(0.011)	(0.028)	(0.028)
Human capital	0.011***	0.003**	0.003***	0.047***	0.049***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
Degree of services	0.001**	0.000	0.001		
subcontracting	(0.001)	(0.001)	(0.001)		
Number of competitors	-0.046***	-0.018*	-0.017*		
	(0.007)	(0.011)	(0.009)		
Age	0.002***	0.001	0.001	-0.004***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Belonging to a group				0.064	0.016
				(0.042)	(0.041)
Initial conditions					
M_Exporter in t-1		0.067*	0.063*		
		(0.039)	(0.035)		
M_Public support in t-1		0.620***	0.618***		
		(0.075)	(0.062)		
M_Demand evolution		0.038	0.033		
		(0.028)	(0.023)		
R&D performer in 0		0.391***	0.317***		
		(0.023)	(0.015)		
Rho				0.120***	-0.201***
				(0.043)	(0.031)
Wald test – Industry dummies	0.000	0.001	0.000	0.000	0.000
Wald test – Time dummies	0.040	0.000	0.000	0.000	0.000
Wald test – Size dummies	0.000	0.000	0.000		
ρ_a		0.119 (0.025)			
LnL	-5165.6	-2774.1	-2789.9	-13078.1	-10684.9
Observed Probability	38.6	38.6	38.6		
Predicted Probability	38.6	38.3	38.6		
Correct predictions	79.9	91.4	91.6		
Correct predictions: 1 / 0	81.8/ 78.7	91.2 / 91.6	90.7 / 92.1		
No. observations	12303	12303	12303	4755	4755

Notes: Marginal effects (standard errors in brackets) are showed. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively. All regressions include a constant and 19 industry and 14 time dummies. Regressions (1) to (3) also include 5 size dummies. To avoid multicollinearity, the dummy variables corresponding to year 1991, industry 1 and size up to 20 employees are excluded. Wald tests report the p-value. The estimates also include four dummies to capture the firm's mobility (merger, scission, entry and exit). Rho is the correlation coefficient, ρ_{12}, and ρ_a is the percentage of total variance explained by the unobserved heterogeneity.

Comparing the first and the second columns, the results show that, when the persistence in the decision to perform R&D activities is taken into account, the degree of services subcontracting and the firms' age, which are strongly significant in the pooled Probit estimation, lose their effect[23]. Both are variables with a small time variation and their effect is probably captured by the lagged dependent variable.

However, there are some explanatory variables which still are significant and increase the probability of carrying out R&D expenditures. Specifically, firms which operate in markets with an expansive demand present a higher probability of engaging in R&D activities. In addition, the proportion of engineers and graduates (as a proxy of skilled employees) confirms the relevance of having qualified workers in the firm to more easily assimilate new knowledge. This result is in line with Peters (2009), who concludes that, in addition to past innovation experience, knowledge provided by skilled employees has a crucial influence on generating innovations over time, confirming the role of innovative capabilities in the dynamics of firms' innovation behavior.

Finally, the number of rivals exhibits a negative sign, which is coherent with the Schumpeterian hypothesis. This result is in accordance with Artés (2009), who, using the same database, analyzes the relationship between different measures of market structure and R&D activity. He also distinguishes between the decision to undertake R&D activities and the decision about the innovative effort, finding that while the latter is not affected by market power, the probability of being a performer increases with it.

As can be seen at the bottom of Table 5, the Wald tests confirm that the control variables are jointly significant. From the coefficients of the size dummies[24], a positive relationship between a firm's size and the decision of carrying out R&D is established. This is consistent with the hypothesis that large firms are more capable of exploiting economies of scale or scope in technological activities, but also with the idea that these firms have advantages in appropriating the results of them and obtaining external funding.

[23] The positive sign of the firm's age in our pooled estimations is in accordance with Artés (2009) and Galende and De la Fuente (2003), which obtain a higher probability of engaging in R&D for older firms. We have also performed additional estimates including the age square to capture non-linearities in the equations for the decision to engage in R&D and for R&D intensity, but in both equations the age square was not significant.
[24] The coefficients are available from the authors upon request.

Due to the fact that estimation in column (2) confirms the existence of true state dependence in the innovation activity and that we are interested in the prediction of the R&D intensity for the second step of the CMD model, we proceed to estimate a Generalized Tobit model with dynamic in the participation equation. Again we parameterize the unobservable heterogeneity following Wooldridge (2005). The results in column (3) are quite similar to the ones in column (2), although the coefficient of the lagged dependent variable is slightly bigger and the number of competitors as a proxy of market competition is now significant as in the pooled Probit.

As can be seen in columns (4) and (5), once the firm has decided to invest, the proportion of engineers and graduates, the winning of public support in the previous period, and the export intensity stimulate the intensity of R&D investment. These results are in accordance with Ortega-Argilés et al. (2005), Griffith et al. (2006) and Hall et al. (2009). However, unlike Griffith et al. (2006), we find that the demand evolution has a positive effect not only on the participation decision but also on the R&D intensity. Additionally, belonging to a group of companies does not affect the amount of R&D expenditures.

The only variable with a negative impact on R&D intensity is the firm's age. This result is consistent with Huergo & Jaumandreu (2004b), who find that although the impact of age is highly non-linear, new firms present on average a high probability of innovating.

The knowledge production function

The second stage of the model corresponds to the estimation of the new knowledge production function (equation [3]) generated from the firm's technological efforts. In Table 6, we show the results of this estimation for three alternative measures of innovation outputs, using the predicted value of R&D intensity (obtained from the estimations in columns (3) and (5) in Table 5) as an explanatory variable. Notice that the R&D intensity equation can be interpreted as an instrumental variables equation, in which innovation effort is presumably endogenous to the innovation production function – that is, there can be unobservable (to the econometrician) firm characteristics that make firms invest more in R&D and, at the same time, make them more productive in the use of this effort. This could generate spurious correlation and upward bias in the coefficients of the knowledge generation equation.

Table 6

The knowledge production function

	Process innovation		Product innovation		Process or Product innovation	
	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	*Static RE Probit*	*Dynamic RE Probit*	*Static RE Probit*	*Dynamic RE Probit*	*Static RE Probit*	*Dynamic RE Probit*
R&D intensity[a]	0.098***	0.047***	0.110***	0.055***	0.139***	0.068***
	(0.020)	(0.016)	(0.016)	(0.013)	(0.024)	(0.019)
Process Innovation in t-1		0.350***				
		(0.012)				
Product Innovation in t-1				0.371***		
				(0.014)		
Process or Product Innovation in t-1						0.374***
						(0.012)
Physical capital intensity	0.110***	0.077***			0.107***	0.076***
	(0.011)	(0.015)			(0.012)	(0.017)
Demand evolution	0.050***	0.043***	0.009	0.008	0.043***	0.035***
	(0.008)	(0.008)	(0.006)	(0.007)	(0.009)	(0.009)
Degree of product homogeneity	-0.034**	-0.018	0.040***	0.042**	-0.014	0.003
	(0.017)	(0.013)	(0.013)	(0.011)	(0.019)	(0.016)
Initial conditions						
M_Physical capital intensity		-0.031*				-0.038*
		(0.017)				(0.020)
M_Demand evolution		0.061***		0.050***		0.076***
		(0.021)		(0.018)		(0.024)
Process Innovation in 0		0.241***				
		(0.015)				
Product Innovation in 0				0.293***		
				(0.018)		
Process or Product Innovation in 0						0.304***
						(0.016)
Wald test – Industry dummies	0.006	0.439	0.000	0.007	0.000	0.359
Wald test – Time dummies	0.000	0.000	0.000	0.000	0.000	0.000
Wald test – Size dummies	0.000	0.000	0.000	0.000	0.000	0.001
ρ_v	0.412	0.122	0.538	0.155	0.467	0.151
	(0.017)	(0.015)	(0.018)	(0.018)	(0.016)	(0.016)
lnL	-6393.0	-5825.7	-5196.0	-4536.4	-6559.2	-5934.6
Observed Probability	35.2	35.2	26.6	26.6	45.5	45.5
Predicted Probability	31.6	34.2	19.6	25.1	43.8	45.0
Correct predictions	66.5	76.5	70.6	81.4	65.0	76.7
Correct predictions: 1 / 0	57.0 / 71.6	74.7 / 77.5	48.1 / 78.7	79.0 / 82.2	61.5 / 68.0	76.7 / 76.7
No. observations	12303	12303	12303	12303	12303	12303

[a] - The prediction of the R&D intensity is obtained from estimations (3) and (5) in Table 5.

Notes: Marginal effects (standard errors in brackets) are showed. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively. All regressions include a constant and 19 industry and 5 size and 14 time dummies. To avoid multicollinearity, the dummy variables corresponding to year 1991, industry 1 and size up to 20 employees are excluded. Wald tests report the p-value. The estimates also include four dummies to capture the firm's mobility (merger, scission, entry and exit). ρ_v is the percentage of total variance explained by the unobserved heterogeneity.

Both for product and process innovation equations, the estimations in columns (2) and (4) also confirm in this case the existence of true state dependence. Conditional on other firm characteristics, a firm which innovates in *t*-1 is around 35 percentage points more likely to innovate in the next period. The last two columns in Table 6 show the results when we do not distinguish between product and process innovation. That is, we consider that a firm obtains a technological result independently of the kind of innovation[25]. As can be seen, the coefficient of the lagged dependent in column (6) is quite similar to those obtained in columns (2) and (4), supporting the existence of persistence.

As we expected, the predicted investment intensity has a significant positive impact on the generation of process and product innovations, even when we consider the dynamics in the generation of innovations. Nevertheless, its impact is smaller when persistence is taken into account. The quantitative effect of this variable is quite similar for process and product innovations. In addition, as in Griffith et al. (2006), physical capital intensity is also positively related to the achievement of process innovation, which is coherent with the fact that part of these innovations are attained through the purchase of new machinery. This variable is also significant when the dependent variable does not distinguish between process and product innovations.

The degree of product homogeneity, used as a proxy of demand price elasticity, presents the correct sign according to theoretical predictions, positive for product innovations and negative for process innovations. However, it loses its significance as a determinant of any type of technological innovation (columns (5) and (6) of Table 6), which can be explained by its opposite effect on product and process innovations.

The Wald tests show that, when persistence is taken into account, there are no significant differences between the probabilities of obtaining process innovations among industries. The size dummies again reflect the advantages of large firms to innovate, and the time dummies denote an increase in the achievement of both types of innovations until 2003, but stagnation during the last two years of the period.

[25] According to this variable, almost 50% of firms have obtained technological results over the period.

The Total Factor Productivity growth

Finally, in Table 7 we present the results of estimating productivity equation [4]. All estimates are carried out considering the information to be a pool. To control for unobserved heterogeneity, we also made complementary estimations, taking into account the panel structure of the data. However, the test for the null hypothesis that all fixed effects are equal to zero cannot be rejected, as is showed at the bottom of the table.

To take into account the potential endogeneity of the technological factor in the production function, instead of observed technological outputs, we include the predicted values for the generation of innovations obtained from the estimations in Table 6 in the specification. The results show that the omission of the persistence in the analysis of the generation of knowledge leads to an overestimation of the impact of innovations on productivity growth.

Specifically, when the predictions from the static RE Probit model are considered (columns (1) and (3) in Table 7), the impact of innovations on the TFP growth is clearly significant, and the quantitative effect is quite similar for both types of innovations. However, when the persistence of innovations is taken into account - columns (2) and (4) - the effect of process innovations on productivity growth is reduced more than fifty percent and the effect of product innovations disappears. Firms which obtain process innovations during the period show a TFP growth significantly higher than non-innovators. In this sense, it seems relevant to consider the true state dependence in the generation of knowledge if we want to capture the real effect of technological outputs on growth.

These results are confirmed when we jointly introduce the predictions for process and product innovations as explanatory variables, as can be seen in column (5) of Table 7. In addition, when we use the prediction for innovation, irrespective of its type, as the only measure of technological output –columns (6) and (7)-, the impact is lower than in columns (1) and (2), in which we consider only process innovations.

Table 7

Total Factor Productivity Growth (IV regression)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Process innovation:							
Prediction from static model	7.250***						
	(1.275)						
Prediction from dynamic model		2.663***			2.825***		
		(0.573)			(0.605)		
Product innovation:							
Prediction from static model			6.686***				
			(1.842)				
Prediction from dynamic model				0.380	-0.460		
				(0.526)	(0.556)		
Process or Product innovation:							
Prediction from static model						6.866***	
						(1.303)	
Prediction from dynamic model							1.722***
							(0.519)
Weighted inputs variation	-0.196***	-0.195***	-0.194***	-0.193***	-0.195**	-0.196***	-0.195***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Capacity utilization variation	0.082***	0.082***	0.082***	0.082***	0.082***	0.082***	0.082***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Merger	5.462***	5.921***	5.854***	6.081***	5.922***	5.715***	6.030***
	(1.151)	(1.146)	(1.148)	(1.147)	(1.146)	(1.148)	(1.146)
Scission	-7.559***	-7.373***	-7.296***	-7.356***	-7.379***	-7.364***	-7.339***
	(1.657)	(1.657)	(1.658)	(1.659)	(1.658)	(1.657)	(1.658)
Entry	0.242	0.407	0.517	0.479	0.394	0.382	0.461
	(0.359)	(0.357)	(0.357)	(0.358)	(0.358)	(0.357)	(0.357)
Exit	-0.384	-0.706	-0.150	-0.839	-0.745	-0.066	-0.696
	(0.574)	(0.569)	(0.602)	(0.571)	(0.571)	(0.588)	(0.570)
Wald test – Industry dummies	0.188	0.068	0.001	0.012	0.080	0.006	0.022
Wald test – Time dummies	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Wald test – Size dummies	0.002	0.236	0.030	0.368	0.276	0.002	0.351
Fixed effects test: F(1071,11212)	0.53	0.52	0.54	0.53	0.51	0.53	0.52
No. observations	12303	12303	12303	12303	12303	12303	12303

Notes: Predictions used in columns (1) to (4) and (6) to (7) are obtained from estimations (1) to (6) in Table 6, respectively. Predictions of process/product innovation used in column (5) are obtained from estimations (2)/(4) in Table 6. All estimates include a constant, 19 industry dummies, 5 size dummies and 14 time dummies. To avoid multicollinearity, the dummy variables corresponding to year 1991, industry 1 and size up to 20 employees are excluded. Wald tests report the p-value. Standard errors (in brackets) are showed. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively.

The positive effect of process innovations is consistent with the evidence provided by Huergo and Jaumandreu (2004a) and Rochina et al. (2010) for the same database. Using semi-parametric techniques, Huergo and Jaumandreu (2004a) find that this type of innovation leads to extra TFP growth of Spanish firms, which also tends to persist somewhat attenuated for three years. With a different methodology –non-parametric methods based on the concept of stochastic dominance-- Rochina et al. (2010) show that the implementation of process innovations produces extra TFP growth both for large and small firms, although this growth is more persistent for large than for small companies.

However, unlike most previous empirical papers on the CDM model, which obtain a significant effect of product innovations -or the share in sales of new products- on labor productivity (see Griffith et al., 2006, and Segarra, 2010, for Spain), the TFP growth seems to be affected only by process innovations. In that respect, our findings show that the choice of the productivity measure is relevant to properly studying the effect of knowledge generation on growth.

The rest of the variables are included in the estimations to control for the non-fulfillment of the assumptions associated with the Solow residual models (constant returns to scale, instantaneous adjustment of the inputs) and the firm’s mobility (entry, exit, merger, scission) during the period. In this sense, the capacity utilization variation is positively related to growth and the negative sign of the weighted inputs variation supports the existence of decreasing returns to scale. In addition, all the mobility dummies show the expected signs but only merger and scission are statistically significant. They have a similar quantitative impact on productivity growth, positive (negative) for mergers (scissions). Although the signs of the dummies for entrants and exiters support the predictions of industry dynamic models, the coefficients are non-significant. Notice that this result can be affected by the fact that we have restricted the sample to firms with more than 7 consecutive observations and therefore we are not capturing all the entries and exits during the period in a suitable way.

5. Conclusions

Since the mid-1990s, productivity in Spanish manufacturing industry has greatly decelerated. This phenomenon, shared with the majority of EU members, keeps European countries away from American firms that have been able to use the new telecommunication and information technologies to improve the efficiency in sectors not directly related to them.

With the objective of clarifying the relationship between technological activities and productivity growth, many researchers have empirically tested, with data from different European countries, the recursive CDM model that explains productivity growth by technological outputs and these outputs by R&D effort. In this line, we estimate an adaptation of the CDM model for a panel of Spanish manufacturing firms during the period 1990-2005. Our main contribution consists of the consideration of persistence both in the R&D investment decision and in the achievement of innovations when estimating the model that reflects the relationship between R&D, innovations and productivity.

The results reflect that the R&D investment status and the production of innovations in one period strongly influence these variables in the next period. The omission of this persistence leads to an overestimation of the effect of the current impact of innovations on productivity growth. In addition, as in Raymond et al. (2010), the significance of the variables we use to approach unobserved heterogeneity confirms the relevance of individual effects in explaining the differences in the firms´ innovative behavior. In fact, when persistence is taken into account, the probabilities of obtaining process innovations do not differ among industries.

Our paper also shows that the choice of the productivity measure is relevant to studying the effect of knowledge generation on growth. Specifically, unlike most previous empirical evidence that finds a positive effect of product innovation on labor productivity growth for Spain (Griffith et al., 2006, and Segarra, 2010), in our analysis only firms which obtain process innovations increase their TFP growth.

These empirical regularities hide important differences in firms’ behavior according to their size. Large firms present advantages in exploiting economies of scope and scale in R&D activities. However, they have more difficulties improving their productivity. Furthermore, the paper shows that the evolution of markets plays a relevant role not only for the probability of engaging in R&D expenditures but also for the effectiveness in obtaining process innovations. Both of them rise when firms perceive their market as expansive.

The estimations also point out the relevance of technological policy as an instrument for increasing productivity. In particular, as improvements in workers' level of education enhance both the probability of carrying out R&D activities and technological effort, and given the evidence of true state dependence in innovation inputs and outputs, firms can be induced persistently to invest in R&D, and therefore to obtain long-term productivity gains, by means of adequate training policies that facilitate access to the skilled workforce.

Second, considering that public support and private R&D investment appear to be complementary rather than substitute activities, subsidies among other public instruments can be used to improve the absorption capability of firms. In addition, just by awarding timely public support, it is possible to induce firms to conduct R&D activities permanently, fostering firms' productivity.

Finally, as the purchase of new machinery seems to stimulate the generation of process innovations through embodied technological change, a complementary way to increase productivity can be to promote investment in physical capital.

References:

Aghion, P., N. Bloom, R. Blundell, R. Griffith and P. Howitt (2005), 'Competition and innovation: an inverted-U relationship,' *The Quarterly Journal of Economics*, **120**, 701-728.

Aghion, P. and P. Howitt (1992), 'A model of growth through creative destruction,' *Econometrica*, **60**(2), 323-351.

Audretsch, D. (1995), *Innovation and Industry Evolution*. MIT Press: Cambridge, MA.

Artés, J. (2009), 'Long-run versus short-run decisions: R&D and market structure in Spanish firms,' *Research Policy,* **38**, 120–132.

Arvanitis, S. and H. Hollenstein (1994), 'Demand and supply factors in explaining the innovative activity of Swiss manufacturing firms,' *Economics of Innovation and New Technology,* **3**, 15-30.

Benavente, J. M. (2006), 'The role of research and innovation in promoting productivity in Chile,' *Economics of Innovation and New Technology*, **15**(4/5), 301-315.

Beneito, P. (2003), 'Choosing among alternative technological strategies: An empirical analysis of formal sources of innovation,' *Research Policy,* **32**, 693-713.

Bond, S., D. Harhoff and J. Van Reenen (1999), 'Investment, R&D and financial constraints in Britain and Germany,' IFS Working Papers W99/05, Institute for Fiscal Studies, London.

Cefis, E. (2003), 'Is there persistence in innovative activities?,' *International Journal of Industrial Organization,* **21**, 489–515.

Cefis, E. and L. Orsenigo (2001), ‘The persistence of innovative activities. A cross–countries and cross–sectors comparative analysis,’ *Research Policy*, **30**, 1139–1158.
Chamberlain, G. (1980), ‘Analysis of covariance with qualitative data,’ *Review of Economic Studies,* **47**, 225-238.
Cohen, W. M. and R. C. Levin (1989), ‘Empirical studies of innovation and market structure,’ in R. Schmalensee and R. Willig (eds.), *Handbook of Industrial Organization,* Vol. 2, North-Holland: Amsterdam, pp.1059-1107.
Crepon, B., E. Duguet and J. Mairesse (1998), ‘Research, innovation and productivity: an econometric analysis at the firm level,’ *Economics of Innovation and New Technology,* **7**, 115-158.
Dosi, G., O. Marsili, L. Orsenigo and R. Salvatore (1995), ‘Technological regimes, selection and market structure,’ *Small Business Economies,* **7**, 1-26.
Duguet, E. and S. Monjon (2004), ‘Is innovation persistent at the firm level. An econometric examination comparing the propensity score and regression methods,’ Cahiers de la Maison des Sciences Economiques v04075, Université Panthéon-Sorbonne (Paris 1).
Esteve, S. and D. Rodríguez (2009), ‘The dynamics of trade and innovation,’ Working paper 467, Fundación de las Cajas de Ahorros: Madrid.
Esteve, S., A. Sanchis and J. A. Sanchis (2004), ‘The determinants of survival of Spanish manufacturing firms,’ *Review of Industrial Organization,* **25**, 251-273.
Galende, J. and J. M. de la Fuente (2003): ‘Internal factors determining a firm’s innovative behaviour,’ *Research Policy,* **32**, 715-736.
Griffith, R., E. Huergo, J. Mairesse and B. Peters (2006), ‘Innovation and productivity across four European countries,’ *Oxford Review of Economic Policy,* **22**(4), 483-498.
Griliches, Z. (1979), ‘Issues in assessing the contribution of R&D to productivity growth,’ *Bell Journal of Economics,* **10**, 92-116.
Griliches, Z. (2000), *R&D, Education, and Productivity*. Harvard University Press: Cambridge, MA.
Hall, B. H. (1992), ‘Investment and research and development at the firm level: does the source of financing matter?,’ NBER Working Papers 4096, National Bureau of Economic Research, Inc.
Hall, B. H., (2002), ‘The financing of research and development,’ NBER Working Papers 8773, National Bureau of Economic Research, Inc.
Hall, B., F. Lotti and J. Mairesse (2009), ‘Innovation and productivity in SMEs. Empirical evidence for Italy,’ *Small Business Economics,* **33**, 13-33.
Hall, B. H., J. Mairesee, L. Branstetter, and B. Crepon. (1999), ‘Does cash flow cause investment and R&D: An exploration using panel data for French, Japanese and United States scientific firms,’ in D. Audretsch and A. R. Thurik (eds.), *Innovation, Industry Evolution and Employment.* Cambridge University Press: Cambridge, pp. 129-156.
Heckman, J. J. (1981), ‘Statistical models for discrete panel data,’ in C. Manski and D. McFadden (eds.), *Structural Analysis of Discrete Data with Econometric Applications*. MIT Press: Cambridge, MA, pp. 114-178.
Himmelberg, C. P. and B. C. Petersen (1994), ‘R&D and internal finance: a panel study of small firms in high-tech industries,’ *The Review of Economics and Statistics,* **76**(1), 38-51.
Hsiao, C. (2003), *Analysis of Panel Data.* Cambridge University Press: Cambridge.
Huergo, E. and J. Jaumandreu (2004a), ‘Firms’ age, process innovation and productivity growth,’ *International Journal of Industrial Organization*, **22**, 541– 559.
Huergo, E. and J. Jaumandreu (2004b), ‘How does probability of process innovation change with firm age?,’ *Small Business Economics,* **22**, 193-207.

Janz, N., H. Lööf, and B. Peters (2004), 'Firm level innovation and productivity—Is there a common story across countries?,' *Problems and Perspectives in Management,* **2**, 184–204.

Jefferson, G., B. Huamao, G. Xiaojing and Y. Xiaoyun (2006), 'R&D performance in Chinese industry,' *Economics of Innovation and New Technology*, **15**(4/5), 345-366.

Klepper, S. (1996), 'Entry, exit, and innovation over the product life-cycle,' *American Economic Review*, **86**, 562-583.

Klette, T. J. and S. Kortum (2004), 'Innovating firms and aggregate innovation,' *Journal of Political Economy*, **112**(5), 986-1018.

Levin, R. C., W. M. Cohen and D. C. Mowery (1985), 'R&D appropriability, opportunity, and market structure: new evidence on some Schumpeterian hypotheses,' *American Economic Review Papers and Proceedings,* **75**, 20-4.

Lööf, H. and A. Heshmati (2006), 'Knowledge capital and heterogeneity in firm performance. A sensitivity analysis,' *Economics of Innovation and New Technology*, **15**(4/5), 317-344.

Mairesse, J. and P. Mohnen (2002), 'Accounting for innovation and measuring innovativeness: an illustrative framework and an application,' *American Economic Review*, **92** (2), 226-230.

Mairesse, J. and P. Mohnen (2005), 'The importance of R&D for innovation: a reassessment using French survey data,' *The Journal of Technology Transfer*, **30**(1–2), 183–197.

Mairesse, J. and M. Sassenou (1991), 'R&D productivity: a survey of econometric studies at the firm level,' NBER Working Papers 3666, National Bureau of Economic Research, Inc.

Malerba, F. and L. Orsenigo (1996), 'The dynamics and evolution of industries,' *Industrial and Corporate Change*, **5**(1), 51-87.

Mañez-Castillejo, J. A., M. E. Rochina-Barrachina, A. Sanchis-Llopis and J. Sanchis-Llopis (2009), 'The role of sunk costs in the decision to invest in R&D,' *Journal of Industrial Economics,* **57**, 712-735.

Mohnen, P., J. Mairesse and M. Dagenais (2006), 'Innovativity: a comparison across seven European countries,' *Economics of Innovation and New Technology*, **15**(4/5), 391-413.

Mundlak, Y. (1978), 'On the pooling of time series and cross section data,' *Econometrica*, **46**(1), 69-85.

Nelson, R. R. and S. G. Winter (1982), *An Evolutionary Theory of Economic Change*. Belknap Press of Harvard University Press: Cambridge, MA.

Ortega-Argilés, R. and R. Moreno (2007), 'Firm competitive strategies and the likelihood of survival. The Spanish case,' Papers on Entrepreneurship, Growth and Public Policy 2007-05, Max Planck Institute of Economics, Entrepreneurship, Growth and Public Policy Group.

Ortega-Argilés, R., R. Moreno and J. Suriñach Caralt (2005), 'Ownership structure and innovation: is there a real link?,' *The Annals of Regional Science*, **39**(4), 637-662.

Ortega-Argilés R., M. Piva, L. Potters and M. Vivarelli (2010), 'Is corporate R&D investment in high-tech sectors more effective?,' *Contemporary Economic Policy*, **28**(3), 353-365.

Parisi, M., F. Schiantarelli and A. Sembenelli (2006), 'Productivity, innovation and R&D: micro evidence for Italy,' *European Economic Review*, **50**(8), 2037-61.

Peters, B. (2009), 'Persistence of innovation: stylised facts and panel data evidence,' *Journal of Technology Transfer*, **34**(2), 226-243.

Piva, M. and M. Vivarelli (2007), 'Is demand-pulled innovation equally important in different groups of firms?,' *Cambridge Journal of Economics*, **31**, 691-710.

Piva, M. and M. Vivarelli (2009), 'The role of skills as a major driver of corporate R&D,' *International Journal of Manpower*, **30**(8), 835-852.

Polder, M., G. van Leeuwen, P. Mohnen, and W. Raymond (2009), 'Productivity effects of innovation modes,' CBS Discussion paper 09033, Statistics Netherlands, The Hague.

Raymond, W., P. Mohnen, F., Palm and S. Schim van der Loeff (2009), 'Innovative sales, R&D and total innovation expenditures: panel evidence on their dynamics,' CIRANO Working Papers 2009s-29, CIRANO.

Raymond, W., P. Mohnen, F., Palm and S. Schim van der Loeff (2010), 'Persistence of Innovation in Dutch manufacturing: it is spurious,' *The Review of Economics and Statistics*, **92**(3), 495-504.

Rochina, M. E., J. A. Mañez and J. A. Sanchis (2010), 'Process innovation and firm productivity growth: does size matter?,' *Small Business Economics*, **34**, 147–166.

Rogers, M. (2006), 'R&D and productivity in the UK: evidence from firm-level data in the 1990s,' Economics Series Working Papers 255, University of Oxford, Department of Economics.

Romer, P. M. (1994), 'The origins of endogenous growth,' *The Journal of Economic Perspectives*, **8**(1), 3-22.

Segarra, A. (2010), 'Innovation and productivity in manufacturing and service firms in Catalonia: a regional approach,' *Economics of Innovation and New Technology*, **19**(3), 233-258.

Segarra, A. and M. Callejón (2002), 'New firms' survival and market turbulence: new evidence from Spain,' *Review of Industrial Organization*, **20**, 1-14.

Utterback, J. (1994), *Mastering the Dynamics of Innovation.* Harvard Business School Press: Boston, MA.

Van Leeuwen, G. and L. Klomp (2006), 'On the contribution of innovation to multi-factor productivity growth,' *Economics of Innovation and New Technology*, **15**(4/5), 367-390.

Wooldridge, J. (2005), 'Simple solutions to the initial conditions problem in dynamic nonlinear panel data models with unobserved heterogeneity,' *Journal of Applied Econometrics*, **20**(1), 39–54.

Appendix: *Variable definitions*

Age: Difference between the current year and the constituent year reported by the firm. We have assigned 40 to firms older than forty years old.

Belonging to a group: Dummy variable which takes the value 1 if the firm belongs to a group of companies.

Capacity utilization variation: Variation in the percentage of utilization of installed capacity reported by the firm.

Degree of product homogeneity: Dummy variable which takes the value 1 if the product supplied by the firm is highly standardized.

Degree of services subcontracting: Variable which indicates the degree of the subcontracted services by the firm not related to its productive activity like legal and fiscal advice, auditing, administration, personal selection and training, computer programming, installing of software packages, courier service, machinery hire, security, cleaning and packing and labeling.

Demand evolution: Each firm identifies the behavior of market demand in its main market during the year with respect to previous years according to three different categories:

recession, stability and expansion. A value of 1, 2 and 3 is assigned respectively to each category.

Export intensity: Ratio of exports over total employment.

Exporter: Dummy variable which takes the value 1 if the firm has exported during the year.

Human capital: Ratio of engineers and graduates over total employment (%).

Number of competitors: Discrete variable which takes the values 1, 2, 3 and 4 when the number of competitors reported by the firm is up to 10, from 11 to 25, more than 25, and in an atomized market, respectively.

Physical capital intensity: Ratio of capital stock in equipment goods to employees.

Process innovation: Dummy variable which takes the value one if the firm has obtained a process innovation during the year.

Product innovation: Dummy variable which takes the value one if the firm has obtained a product innovation during the year.

Public support: Dummy variable which takes the value 1 if the firm has obtained public funding during the year.

R&D intensity: Ratio of total expenditures in R&D (including technology imports) over total employment.

R&D performer: Dummy variable which takes the value 1 if the firm has positive expenditures in R&D during the year.

Size: number of employees of the firm during the year.

Total factor productivity growth (Solow residual): It is calculated using the Tornqvist index: $TFP = y - s_L l - s_K k - s_M m$, where the output and the inputs are in logarithmic differences and the weights *s* in t are the cost shares of each input in the year *t*. Intermediate consumption variation (*m*) includes raw materials, services purchases and energy and fuel cost. Output and intermediate consumption are deflated using Paasche-type firm individual indices, constructed starting from the price changes in output and inputs reported by firms. Labor input variations (*l*) are the changes in total effective hours of work (normal hours plus overtime hours minus lost hours). Physical capital variations (*k*) are the changes in net stock of capital for equipment goods in real terms, that is calculated by using the perpetual inventory formula: $K_t = (1-d)K_{t-1}(P_t / P_{t-1}) + I_t$, where *P* is the price index for equipment, *d* is the depreciation rate, and *I* is the investment in equipment. The user cost of capital is calculated as the long-run debt interest rate paid by the firm plus equipment good depreciation minus the rate of change of a capital goods price index.

Weighted inputs variation: It is calculated as $s_L l + s_K k + s_M m$. See the definition of *TFP growth*.